

THE JOURNAL OF TRANSPORT AND LAND USE <http://jtl.org>
Vol. 13 No. 1 [2020] pp. 299–316

JTLU

Impact of land use on bicycle usage: A big data-based spatial approach to inform transport planning

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Abstract: Bicycling is an alternative of urban transport mode, which is significantly influenced by land use. This paper makes an effort to quantify the magnitude and direction of the impact. We first develop a theoretical framework to establish links between land use and bicycle usage. Then, trip data is crawled from *Mobike*, one of the largest newly emerging, free-floating bike sharing operators in Shenzhen (China), for a total of more than 7.8 million records over 191 consecutive days. And bicycling frequency, travel duration, and riding distance are obtained to be proxies of bicycle usage. Land-use characteristics regarding bicycling are comprehensively indicated by a set of standardized variables including three dimensions, land-use type, land-use mix, land-use connections, and 12 concrete indices. Panel spatial model is applied to quantify the associations at the district level with socioeconomics controlled. Results show that the percentage of green land has a remarkable impact on bicycle usage outcomes and land-use mix is positively associated with bicycling frequency. Density of intersections contributes to longer trip duration. Bicycle lane is a positive facilitator on workdays, while the number of stations is positively related to bicycle usage, especially frequency and distance. These findings provide insight into land use-transport interaction and could be of value to policymakers, planners and practitioners for transport planning while incorporating bicycling-friendly principles.

Keywords: Land use, bicycle usage, panel spatial regression, transport planning, China

Article history:

Received: December 2, 2018

Received in revised form:

September 10, 2019

Accepted: January 31, 2020

Available online: November 6,
2020

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<http://dx.doi.org/10.5198/jtl.2020.1499>

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The *Journal of Transport and Land Use* is the official journal of the World Society for Transport and Land Use (WSTLUR) and is published and sponsored by the University of Minnesota Center for Transportation Studies.

1 Introduction

Bike sharing plays an increasingly important role to sustainable transport system. As a necessary component of transportation in the vehicle-leading society, it not only benefits human body but also reduces carbon dioxide emissions to a large extent. About a third of motorized travel is less than 5km which have potential to be covered by bicycling with no fossil fuel consumption, and thus eases traffic pressure (Yang & Zacharias, 2016; Zacharias, 2005). These unique merits make authorities and practitioners to promote and innovate bike sharing service continuously. Therefore, understanding and identifying the determinants of bike usage have been topical issues attracting growing attention.

Past half century has seen evolution of bike sharing service for three generations (DeMaio, 2009; El-Assi, Mahmoud, & Habib, 2017). The chequered history starts with a number of white painted bikes in Netherlands (Shaheen, Guzman, & Zhang, 2010). These unlocked white bikes were put in circulation to be used for anyone free of charge. Based on coin-deposit system, the second-generation bike sharing is improved by introducing docking stations for unlocking, payment, and return bikes (Zhang, 2010). With the new progress of information and communication technology (ICT), it is possible for cashless payment and dynamic pricing schemes with smartcards connected to sophisticated docking stations or pole. However, the usage rate of conventional bike sharing stay low mainly due to the constraint of dock (Shaheen, Cohen, & Martin, 2013). By February 2012, the number of third-generation bikes is just over 0.18 million in China. It is not so successful as expected until the emergence of free-floating bike sharing (FFBS) currently in China. This service has experienced a rapid expansion since 2016 and heads for other cities worldwide such as Singapore, Sydney, Manchester, San Francisco. Operators of FFBS sprang up in succession from June 2015, among which start-up company *Mobike* is the one of the most popular. The provider possesses approximately 4 million shared bikes cover 80 cities and accumulated 3 billion orders by 2017, accounting for 56.56% of the total marketing share (Wang & Zhou, 2017).

The new generation of bike sharing service is revolutionizing the traditional bike sharing without docking stations. The constructive features of FFBS make renting and return more convenient and effective (Karki & Tao 2016; Shen, Zhang, & Zhao, 2018). With embedded GPS sensor reporting real-time locations, bikes of FFBS can be easily found by potential riders via a smart phone. Registered consumer can use App (mobile application program) to unlock the bike by scanning its QR code and start the ride. Dynamic pricing is completed by mobile cashless payment. Upon arrival at the destination, the bike can be parked “anywhere” allowed at user’s convenience such as roadside, building around. Unrestricted by the capacity of docking stations, the scale of supply is far beyond actual need. Idle bikes occupy public space especially the pavement, which not only lead to a waste of social resource but also reduces the traffic fluency (Kutela, & Kidando, 2017; Kaspi, Raviv, & Tzur, 2016).

Using a fresh big data of trips harvested from FFBS, this paper makes an effort to further the understanding of bike usage from perspective of land use. Specifically, we firstly develop a theoretical framework to establish links between land use and bicycle usage of FFBS. And the spatiotemporal dynamics of bicycling trips are depicted based on the harvested data from *Mobike*, Shenzhen. Then, a set of variables is selected to capture land use characteristics regarding bicycling. Panel spatial regression model is employed to quantify the association between different land use and bicycle usage indicators. On this basis, we also discuss some critical implications for transport planning. The rest of this paper is arranged as follows: Section 2 is literature review and we explain why our work is innovative, section 3 demonstrates materials and methods, especially the details of data collection. We report empirical results in section 4 and discuss in section 5, followed by a conclusion in Section 6.

2 Literature review

2.1 An overview of bike sharing

A growing number of researches focus on bike sharing in terms of various aspects towards sustainable transportation. It seems undoubtedly that bike sharing generates environmental, social and health benefits such as emission reduction, flexible mobility, physical exercise and financial savings (Midgley, 2011; Shaheen et al., 2010; Shaheen et al., 2013). Several studies have quantified the benefits of green house gas (GHG) emission reduction (Kou, Wang, Chiu, & Cai, 2020). For example, DeMaio (2009) explicitly figured out that the bike sharing in Montreal had reduced carbon emissions by over 1300 tons since its initiation. Some studies conduct a comparative analysis of different cities with regard to characteristics of flows, share changes, and so forth (Zhang, Zhang, Duan, & Bryde, 2015; O'Brien, Cheshire, & Batty, 2014). Krykewycz, Puchalsky, Rocks, Bonnette, and Jaskiewicz (2010) propose a sophisticated approach for demand forecast of shared bikes. Using the social network analysis method, Shi, Si, Wu, Su, and Lan (2018) identify the stakeholder-associated critical factors and their interactions to provide implications for FFBS sustainability. Some other studies pay attention to rebalancing problems (Faghih-Imani, Hampshire, Marla, & Eluru, 2017), infrastructure investment (Grisé & El-Geneidy, 2018) and so on. These system-level efforts can provide useful references for program installing decision and management while coordinating existing systems.

More previous studies focus on the influencing factors of bike sharing usage. Though bicycle usage varies greatly with social indicators, FFBS has promise for offering equitable access (Tan, Zhao, & Huang, 2019; Mooney et al., 2019). Socioeconomic demographics such as population density, household income, and car ownership have been evidenced to influence the usage of shared bike (Buck, & Buehler, 2012). And, job density plays an similar role (Rixey, 2013). As to built environment, some publications pay attention to infrastructure that traditional bike sharing systems heavily rely on. Increasing number of stations is identified as a stimulus to bicycling departure (Buck, & Buehler, 2012; Faghih-Imani, Eluru, El-Geneidy, Rabbat, & Haq, 2014; Wang et al., 2016). Except for total number, capacity (the number of docks per station) may give a further account of users' ridership (El-Assi et al., 2017). However, the impact of facilitation may also come from the surrounding environment—for example, bicycle routes around stations (Wang et al., 2016) and higher number of POI (such as restaurants, retail stores) in the vicinity (Rixey, 2013; Faghih-Imani et al., 2014). Furthermore, stations in areas with higher land use densities, mixture, and adequate commercial land may attract more riders (Wang & Akar, 2019). In addition to social demographics and built environment, temporal characteristics and weather conditions such as wind, precipitation and temperature are confirmed to have remarkable influence on the usage of shared bike (El-Assi et al., 2017; Gebhart & Noland, 2014; Kutela & Teng, 2019). These efforts aid authorities in locating more bike stations and promoting usage of shared bikes as they point out the factors of enhancing ridership.

2.2 Theoretical links between land use and bicycle usage

It is widely accepted that land use should harmonize with public transport planning in order to provide a sustainable urban transport system (Nigro, Bertolini, & Moccia, 2019). Land use measures are deemed as effective means to promote the use of non-motorized transport modes (Wang, Chai, & Li, 2011; Mitchell & Rapkin, 1954). It therefore requires for a good knowledge of the connection between land use and bicycle usage. Related research efforts are devoted on the statistical correlations between land use and bicycle usage. Strong linkages are found to support theoretical causality (Giles-Corti, Timperio, Bull, & Pikora, 2005). Based on an extensive literature review, a theoretical framework is firstly devel-

oped to explore the impact of land use on bicycle usage (Figure 1).

- Land use types burdens various specific function and cyclists are exposed to integrated environment represented by neighboring land use types (Durstine, Gordon, Wang, & Luo, 2013). Therefore, land use types not only distribute the departure point and destination but also affect intensity of riding willingness. Previous studies have made efforts on various bicycle flows attracted by different land use types. For example, green land (e.g., parks, groves, lawn) has been reported to be positively associated with bicycle usage (Frank et al., 2006), and proximity of green space increase the times of cycling (Fraser & Lock, 2011). Moreover, commercial land has been suggested to call for more cyclists. Several studies found that the number of restaurant in close to bike station increases the usage (Faghih-Imani et al., 2014). A Canada study is consistent with this results, and additionally, it argued that recreation and business land are important contributors (Faghih-Imani et al., 2017). On the contrary, station distance to CBD (central business districts) shows a negative correlation with the arrival rates (Faghih-Imani et al., 2014). The presence of nearby commercial land-uses is relate to low rate of vehicle ownership (Cervero, 1996). Similarly, stations near universities are prone to receive more bicycles arrivals (Wang, Lindsey, Schoner, & Harrison, 2015). In a Dutch study, cycling for transport was encouraged by the square area of parks (Wendel-Vos et al., 2004).
- Land use mix, at the landscape level, is positively associated with bicycle usage according to existing evidence. Land use types could shape commuting behaviors and influence transportation mode choice (Christian et al., 2011). And, non-auto commuting is more encouraged by mixed land-uses (Cervero, 1996). A case of Northern California confirms that residents of neighborhoods with higher mix of land use drive less than districts with lower (Handy, Cao, & Mokhtarian, 2005). Particularly, residents are more prone to bicycling if there is grocery stores or other services within 300 feet of one's habitation (Cervero, 1996). On the other hand, as the two import mode of non-auto transportation, bicycling can easily cover the distance of walking. The essence of mixed land use is the variety of functions in a certain area. In general, high level land use mix and diversity indicate the greater access to services and facilities which can be easily covered by cycling (Duncan et al., 2010). Besides, residents within higher land use mix are reported to have more social engagement and outdoor activities. This reason has increased short-distance travel demand in turn leads to more bicycle usage. Land use mix is found significant associations with physical activity (Frank, Schmid, Sallis, Chapman, & Saelens, 2005). If land use measurements are taken to improve mixture of land use, people may be more likely to drive less and bicycling more.
- Land use connections, which including bicycle-friendly physical conditions and street connectivity, play a fundamental role in cycling progress. Bicycle-oriented infrastructure or facility improvements (such as paths, lanes) are found to be dramatically correlated with increased bicycle usage (Ma & Dill, 2015). Moreover, the street connectivity has been recognized to be a positive impactor of bicycle usage in that higher street connectivity and network density may provide multiple routes and thus it substantially reduces trip distance (Southworth, 2005), which indicate more accessibility and flexibility, and thereby increase commuter cycling (Saelens, Sallis, & Frank, 2003; Heinen, Van Wee, & Maat, 2010). Consequently, increased land use connections are correlated with increased bicycling (Marshall & Garrick, 2010). Furthermore, the presence of metro stations connects more bicycle users (Nair, Miller-Hooks, Hampshire, & Bušić, 2013). Similarly, cycling was positively associated with the degree of bike lane connectivity (Titze, Stronegger, Janschitz, & Oja, 2008).

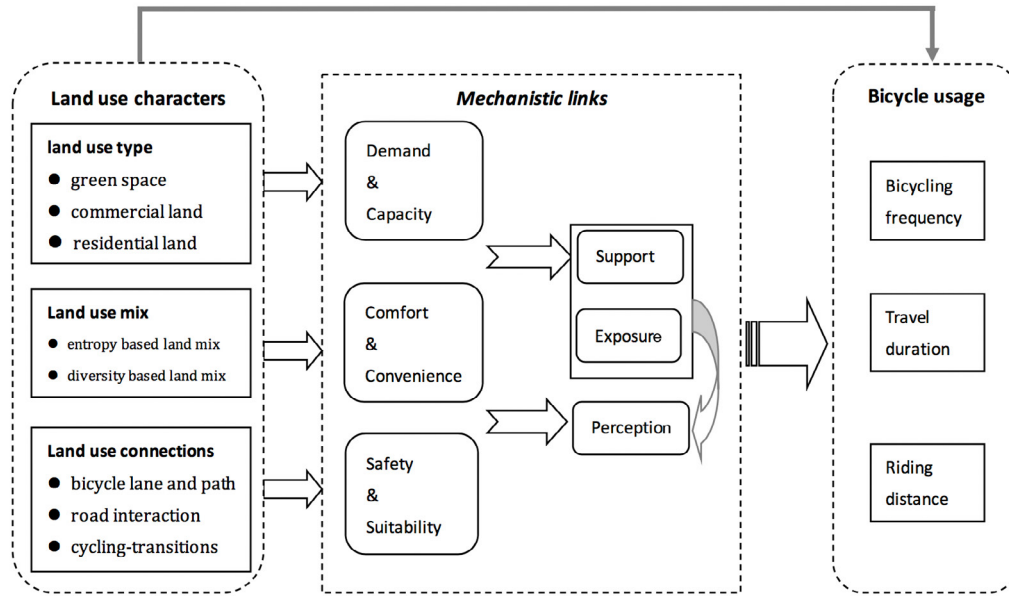


Figure 1. The theoretical framework of land-use characters linked to bicycle usage

2.3 The contributions of present study

Owing to the computational complexity and data requirement, most existing researches are accomplished with data compiled from station-level observations or survey (Fraser & Lock, 2011; Faghih-Imani et al., 2014). These evidences are of significance for management of the traditional bicycling sharing system. However, whether it is applicable for dockless FFBS remains to be investigated and need further targeted researches. What's more, relationship between built environment and bicycling shows mixed results in western cities and research efforts are limited especially in developing countries (Zhao, 2014). Although land-use determinants are previously incorporated into built environments (Cervero & Kockelman, 1997), the efforts from the perspective of land use are not enough. And there is a need for systematic and comprehensive research.

Recently, the number of studies regarding FFBS is increasing rapidly. FFBS is a harbinger of things to come, we see the necessity to re-identify and re-assess the association to achieve the sustainable transport planning under the new situation. For one hand, bicycle usage is so much different that prior knowledge presents some limitations. By contrast of previous trajectories between piles, now it exists on every piece of land. Usage habits and influencing factors are thus not alike. For another, with increasing prevalence of FFBS, there are some new challenges. The new ICT technology provides a larger body of trip data than ever, which is a golden opportunity to achieve more accurate and inclusive estimations, especially from perspective of land use. We extract land-use indicators from three domains at district level: land-use type, land-use mix and land-use connections. As land-use measurement is forceful tool for transport planning and urban management, our work can be of value for policy makers and transport practitioners to achieve goals while incorporate bicycling principles.

3 Materials and methods

3.1 Study area

Shenzhen, located in the southern coast of China, inhabits more than 12.52 million population with an area of 1997.47km² (Shenzhen Statistical Yearbook, 2018) (Figure 2). The past three decades have seen the rocket-like urbanization as well as the explosion of population and cars in Shenzhen. In order to cope with the challenge, Shenzhen has improved the urban transport infrastructure and laid much stress on no-motorized system. Urban public services are distributed in view of segregated classes (You, 2016). It has made dramatic advances in administration and been titled “international garden city” and “livable city”. In addition, Shenzhen signs post on the path to “Smart city” and breeds a number of internet technology companies, Tencent, for instance. The popularity of mobile internet to a high extent makes FFBS widely used in short travel and cyclists' habits are relatively stable. According to Shenzhen Traffic Police Bureau, the number of shared bikes is about 520 thousands covering all blocks in Shenzhen. Registered users amount to 9 million, and daily average usage is about 5.43 million person-times (Data source: http://sztqb.sznews.com/html/2017-04/24/content_3775917.htm). Abundant data increases accuracy and reliability of the estimated results. These features make Shenzhen a typical case to exam the association between land use and bicycle usage. Additionally, Shenzhen is divided into 57 districts (called “jiedao” in Chinese), and district is the basic unit of census. Besides, given that bicycling distance is usually within 5km, district-level is fine geographic scale to investigate the bike usage.

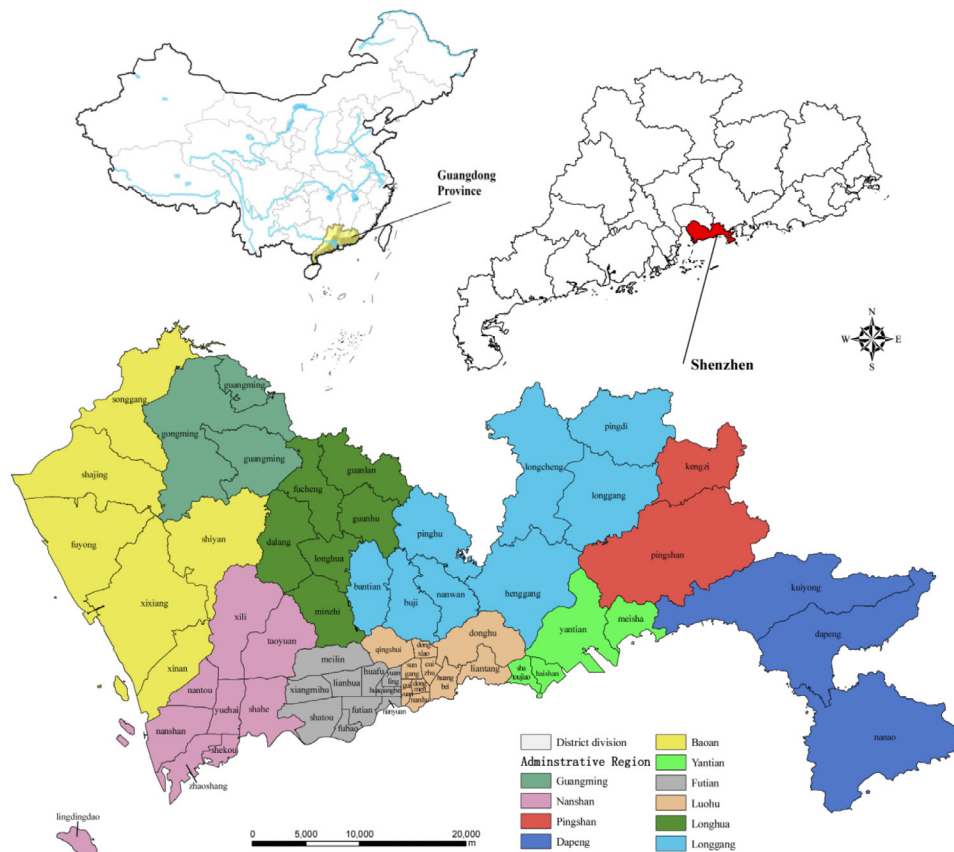


Figure 2. The location and districts division within Shenzhen

3.2 Bicycle usage and data collection

The indicators of bicycle usage vary from different researches. Pioneering efforts focus on the odds of bicycling at group level (Winters, Davidson, Kao, & Teschke, 2010), or the prevalence of cycling (Sisson, Lee, Burns, & Tudor-Locke, 2006). Similar is the decision to ride or mode choice (Winters, Brauer, Setton, & Teschke, 2011). Other studies pay attention to travel duration, time allocation (Castillo-Manzano, López_Valpuesta, & Sánchez-Braza, 2016). In addition, speed, trip distance (Mateo-Babiano et al., 2016), or so called miles traveled, and trip length are also investigated (Ewing & Cervero 2012). In general, the key points of bike usage can be categorized into frequency, time and distance, which account for our explained variables given data availability.

A crawling tool programmed by Python is used to visit API (Application Programming Interface) of *Mobike*, one of the largest operators around the world. In virtue of crawler, we traversed the location coordinates of bikes in 57 districts of Shenzhen every 5 minutes through the API of *Mobike*. Considering privacy, all bikes identified by a ten-digit ID without personal information (for example, 7557558888: the first three figures represent the initial launch site). Bikes which are unable to be detected are deemed in use currently. If two locations are significantly distant (threshold is 20m), the bike is assumed to complete one riding. By sorting the GPS coordinates with timestamp, we can extract the movement of a bike in one day and thus get frequency of bikes. Then, the origin-destination pairs obtained are fed in Baidu map, a prevailing navigation service application in China, to get planning path of simulating bicycling. Consequently, travel duration and riding distance are harvested from riding trajectory. The project started at 6:00am until 12:00pm local time from June 17 to December 24, 2017.

However, the raw data contain some errors or redundancy. Several preprocessing steps are taken to increase data reliability. Given the influence of GPS drifting, linear distance between two coordinates less than 20 meters are removed as false data. Furthermore, we discard the recordings in gale or rain-storm, on which it was not suitable for bicycling, to eliminate the impact of bad weather. Lastly, abnormal trips that might not be an actual riding are excluded given that some extremely long-distance trips could result from relocation by operators. In addition, following Shen et al. (2018), we abandon the trips beyond the range of 20m to 5km or longer than 60 minutes. It is worth noted that 99.8% data are valid cycling trips. Finally, we have drawn 7,821,523 records from 392,956 bikes covering 57 districts in Shenzhen for 191 days.

Thermodynamic chart is conducted on the raw data of total bicycling frequency. As shown in Figure 3, bicycle usage exhibits great disparities in space. In particular, Nanshan, Futian, Luohu are recognized as hot spots. Baoan, Longhua and Longgang are moderate zone, while Dapeng, Pingshan, Yantian and Guangming are deserted areas. It suggests a subtle link between bicycling and land use.

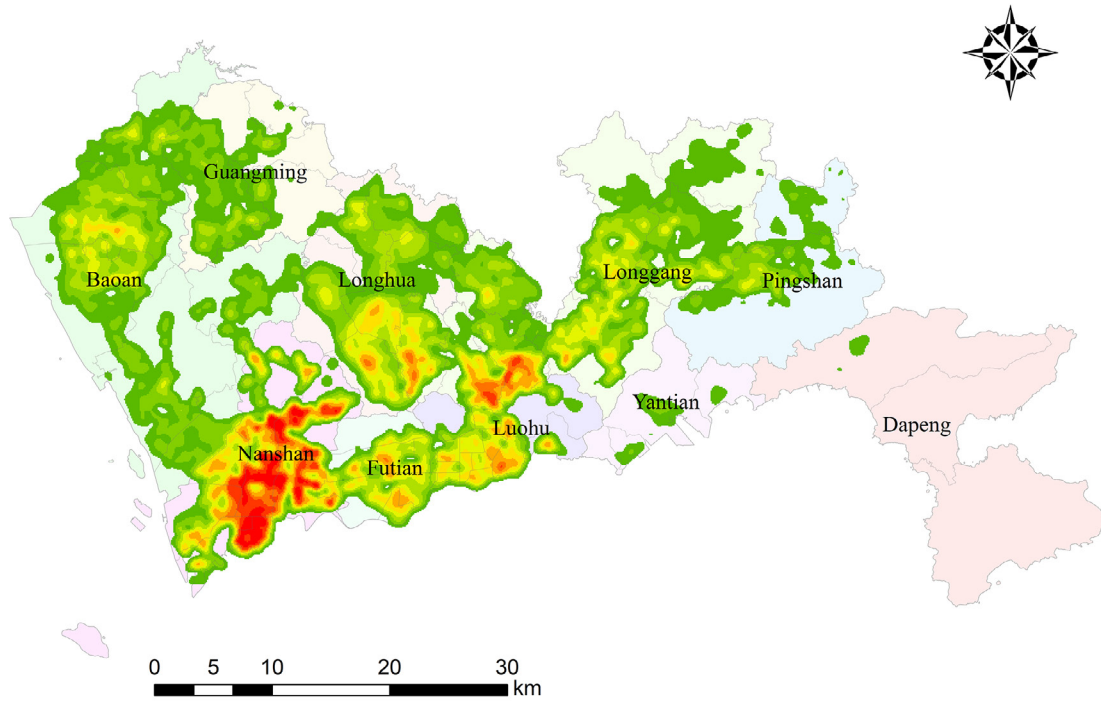


Figure 3. The spatial distribution of bike trips within Shenzhen

3.3 Panel spatial regression

In earlier studies of bike sharing system, the spatial interactions of neighboring stations are identified and incorporated in modeling estimates to improve the demand forecast (Rudloff & Lackner, 2014). More efforts have considered temporal change using time series data (Nair et al., 2013) to predict the local demand. Faghih-Imani and Eluru (2016) believe that neglecting such effects will result in biased model estimations when they are actually present. As to our sample, the bike utilization within district is affected by surroundings and supply. This spatial-temporal effect stems from that dockless bikes always inevitably flow across districts and supply thereby changes in real-time; Similar meteorology factors conditions are in districts of city; And other factors unobserved. Thus, we take spatial effects in analysis by employing spatial panel models. Specifically, the spatial regression model incorporating two main forms, namely spatial lag model (Eq.1) and spatial error model (Eq.2). Spatial leg model suggests that bicycle usage within one district depend on that of neighborhood. Alternatively, if there are unobserved variables which impact the bicycle usage, a spatial error model may fit.

In our case, there are 57 districts (statistic unit) in Shenzhen. Let $q=1,2,3,\dots, Q(Q=57)$ to represent each district and $t=1,2,3,\dots, T$ ($T=131$ working day, $T=60$ off days and $T=191$ for total days) for each period. The sample makes for a panel structure of 191 repetitions (131 working days, 60 off days) per district. Spatial panel regression model can be written as:

$$B_{qt} = \delta \sum_j W_{qj} B_{jt} + \alpha L_q + \beta C_q + \gamma S_{qt} + \mu_q + \varepsilon_{qt} \quad (1)$$

$$B_{qt} = \alpha L_q + \beta C_q + \gamma S_{qt} + \mu_q + \varphi_{qt} (\varphi_{qt} = \delta \sum_j W_{qj} B_{jt} + \varepsilon_{qt}) \quad (2)$$

Where B_{qt} is the dependent variable indicating long-normal of bicycle usage; L_q denotes explanatory variables for land-use determinants within district q ; S_{qt} is the supply of FFBS in district i at time t , it is counted by unique ID during period t in district i ; α β γ are the corresponding coefficient; μ_q represents other land-specific but time-invariant unobserved attributes. We treat this spatial effects as random effects. Where δ represents spatial autoregressive coefficient, W_{qj} is a spatial weight matrix and φ_{qt} accounts for the spatial autocorrelated error term. Before executing models, the robust Lagrange multiplier tests (LeSage, 2008) are adopted to select the specific model form, lag model or error. Due to the possible multicollinearity, variance-in-inflation method is used to select the input variables. Besides, we employ the nearest neighbor distance approach, which is capable of incorporating more spatial information (Su et al., 2013), to construct the spatial weighted matrices. All the operations are executed in the Matlab2016a software.

3.4 Variable selection

3.4.1 Land-use indicators

Considering the existing related research and the theoretical analysis, this paper measures land use at district level from three dimensions including land-use types, land-use mix and land-use connections. Six variables from three domains are chosen to describe land-use types: percentage of urban public green land (e.g., park, grove), percentage of commercial land, percentage of residential land, percentage of blue land (e.g., rivers, lakes, wetland and artificial water), percentage of institutional land (e.g., university, hospital, museum and gymnasium), percentage of industry land. The Simpson's diversity index (Eq.3) and the entropy index (Eq.4) are widely used to calculate land-use mix based on all land-use types (Su, Zhang, Pi, Wan, & Weng, 2016), we adopt them both to indicate land-use mix. Land-use connections are indicated by the density of intersections and road network, which are separately computed by the number of intersections per km² and road length per km². In particular, we calculate the length of bicycle lane and number of stations (bus stations and metro stations) per km². Data of land-use variables are extracted from Shenzhen Digital Map (2017). The descriptive statistics of land-use indicators is as shown in Table 1.

$$D=1-\sum (n/N)^2 \quad (3)$$

Where D is the Simpson's diversity index; n is the number of a certain land-use type; N is the total number of all land-use types.

$$M=\frac{1}{\ln(n)} \sum_{i=1}^n P_i \ln(P_i) \quad (4)$$

Where M is the entropy index; P_i is the percentage of land-use type i ; n is the total number of types.

Table 1. Descriptive statistics of land-use indicators

Domains	Variables	Unit	Max	Min	Mean	SD
Land-use type	PUPG	%	73.21	17.64	45.08	6.75
	PRL	%	38.74	16.90	25.16	5.83
	PCL	%	17.56	5.85	10.62	3.11
	PBL	%	0.65	0.01	0.23	0.31
	PIL_ins	%	0.08	0.01	0.51	0.17
	PIL_ind	%	0.36	0.00	0.25	0.16
Land-use mix	SDI	1	0.88	0.04	0.38	0.12
	MEI	1	0.73	0.05	0.26	0.18
Land-use connections	DI	1/km ²	6.32	0.00	3.15	1.44
	DRN	1/km	5.75	0.89	3.17	0.19
	LBL	1/km	0.39	0.08	0.11	0.22
	NPTS	1/ km ²	0.21	0.01	0.09	0.32

Abbreviations: percentage of urban public green space (PUPG), percentage of residential land (PRL), percentage of commercial land (PCL), percentage of blue land (PBL), percentage of institutional land (PIL_ins), percentage of industry land (PIL_ind), the Simpson's diversity index(SDI), the entropy mix index (EMI), density of intersections (DI) and density of road network(DRN), the length of bicycle lane (LBL), number of public transport stations (bus stations and metro stations) per area (NPTS)

3.4.2 Control variables

Past efforts have demonstrated that various neighborhood socioeconomics have effects on bicycling. These effects are difficult to be isolated and may result in estimation bias if ignored. Given such challenge, we have referred to empirical evidence and selected 4 essential control variables of socioeconomics. For example, total permanent inhabitants (Rixey, 2013), car ownership rate (Wang et al., 2011), average income (Fuller & Winters, 2017), and percentage of young and middle-aged people (aged from 18 to 45) (Zhao & Li, 2017). All the raw data of socioeconomics are provided by Shenzhen Census Bureau (<http://tjj.sz.gov.cn/>).

4 Results

Table 2. Standardized coefficients of land-use variables estimated by spatial regression (N=57)

Variables	weekday			Weekend			Total		
	Bicycling frequency	Travel duration	Riding distance	Bicycling frequency	Travel duration	Riding distance	Bicycling frequency	Travel duration	Riding distance
PUPG	0.185*		0.032*	0.036***	0.237***	0.192**	0.073***	0.255**	0.172***
PRL	0.197**	-0.103*					0.156***		
PCL	0.204***			0.314*	-0.121***	-0.031*	0.143*	-0.133**	0.080***
PBL		0.091***	0.112**	-0.103*	0.208*	0.004**		0.058*	
PIL_ins								0.007*	0.095***
PIL_ind					0.109**				0.001*
SDI	0.173*		0.112*				0.277***		
EMI	0.236***	0.011**	0.154***	0.099*		-0.082**	0.041***		0.050**
DI	distance	0.183*						0.011***	
DRN	0.104*		-0.072***	0.139**	-0.173**	0.100*	0.099*		0.188*
LBL	0.395**	0.108***	0.205**				0.141*	0.057*	0.244***
NPTS	0.519*		-0.336**	0.298*	-0.117***		0.125***	-0.191***	0.151***
Spatial Dependency	Lag	Error	Lag	Lag	Error	Lag	Lag	Error	Lag
R ²	0.17	0.35	0.24	0.39	0.08	0.41	0.12	0.59	0.28

Lag: spatial lag regression; Error, spatial error regression.

Significantly at *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$.

The control variables are not reported for simplification.

Although coefficients vary from land-use indicators greatly, we do find significant relationships between land use and bicycle usage. As shown in Table 2, some key land-use variables are identified and there is a difference between weekday and weekend. To be specific, percentage of green land shows a significant correlation with the majority of bicycle usage outcomes except travel duration on workday. The percentage of residential land and percentage of commercial land are noticeably associated with bicycling frequency on workdays, while the latter presents negative correlations with travel duration and riding distance at weekend. Percentage of blue land is positively related to the travel duration and riding distance, percentage of institutional land and percentage of industry land are also closely linked with them. Riders tend to spent more time in proximity of blue land. Additionally, land-use mix is positively connected with bicycling frequency. It demonstrates that higher bicycling frequency is more likely to be observed in districts with higher land-use mixture. Results show that the density of intersections is dramatically linked to travel duration. It indicates that increasing number of intersections leads to longer riding time. The bicycle lanes are positively related with the three bicycling variables on workdays. It denotes that weekdays witness more individuals taking a ride on road with dedicated lane. Number of stations is positively related to bicycle usage, especially the frequency and distance. It is evidenced that the bicycle-friendly facilities play an important role in FFBS promotion.

5 Discussion

5.1 Land-use determinants of bicycle usage

Using the spatial regression, we have obtained several results that are similar to previous studies. It is discovered that high bicycling frequency is found in districts with higher percentage of green land. It is consistent with the argument that belt, parks or other green land are the attractive conditions for cyclers (Titze et al., 2008). This may owing to comfortable and joyful physical environment which are free from noise and air pollution, therefore it is more suitable for bicycling and other outdoor activity (Sugiyama, Leslie, Giles-Corti, & Owen, 2009). It is supported by results that percentage of green land demonstrates stronger relations with bicycle usage at weekends. The result that bicycling lane facilitates bicycling supports the proposal of providing more infrastructure aiming at bicycling promotion (Faghih-Imani, et al., 2014). Most possibly, it comes down to security consideration, which have been a major concern for traveler (Chahal, Harit, Mishra, Sangaiah, & Zheng, 2017). Bicycling lane is not only physical conditions for cyclers, but also a necessary protection from traffic perceived in an Austrian study (Titze, Stronegger, Janschitz, & Oja, 2007). Land-use mix is also found to be an important factor to encourage bicycling. Since mixed land use carries production, residence, service and many other features satisfying people's daily demands nearby, which greatly reduces commuting distance to extend that is suitable for bicycling (Chillón, Molina-Garcia, Castillo, & Queral, 2016). By and large, land-use connectivity has positive correlations with bicycling frequency. Past studies have confirmed that physical street conditions could promote social contacts and outdoor activities (Su et al., 2016), thus leading to a corresponding increase in bicycling.

However, there is no consistent conclusion about the role of bicycling infrastructure in western cities (Sun & Zacharias, 2017). Our effort provides a possible explanation by separating weekday and weekend in case of Shenzhen in developing China. Different time periods mean different travel purposes. Usually, inhabitants ride for work on weekdays for work on weekday and for recreation at weekend. For different purpose of bicycling, commuting or recreation, the infrastructure plays different role (Sun & Zacharias, 2017; Zhao, 2014). Results demonstrate that bicycling lane and density of road network tend to increase bicycle commuting while decrease that of recreation at weekend. It is worth mentioning that public transit services (public transport stations, e.g., bus stations and metro stations) are likely to increase the bicycling according to our results, which is contrary to previous research (Zhao, 2014). The bicycle-transit integration has been a growing mode to transport in crowded cities (Zhao, 2017). Perhaps, the convenience of FFBS makes a difference that parking around the stations frees cyclists from bike secure, which is a plague for riders in the past (Faghih-Imani et al., 2014).

We also have found several remarkable factors of travel time and riding distance. Firstly, percentage of blue land has positive effects on travel duration and riding distance, especially at weekend. It implies that the water view is important for entertainment and protection of rare water landscape should be strengthened. Secondly, increasing number of intersections leads to longer riding time. Perhaps, traffic lights of intersections in Shenzhen have increased waiting time and decreased the traffic capacity. Thirdly, travel duration and riding distance are negatively with percentage of commercial land, percentage of residential land, density of road and number of stations, which is a driver of opposite direction comparing with that of the frequency. In fact, residents on weekday are in pursuit of speed in modern fast-paced life and cycling more for short commuting. At weekend, the green land attracts the cyclist to spent more time on enjoying life (Heesch, Giles-Corti, & Turrell, 2015). In addition, our findings shed light on the mediating effect that bicycling is a bridge between land use and public health. On one hand, it has been amply confirmed by medical science that rhythmic contraction of leg muscles when ride a bike can enhance the pumping function of heart, respiratory and immune systems (Eriksson, Uddén,

Hemmingsson, & Agewall, 2010). On the other hand, bicycling for outdoor in green land is a wholesome choice for recreation. Moreover, bicycling could reduce pollutant discharge and in turn benefits human body.

5.2 Implications for bicycle-friendly transport planning

The complicated links between land use and transportation is well established, this interaction accounts for traffic-inducing problems from perspective of land use. Integrating land arrangements into transport planning in turn offers some hopes of mitigating the negative influence (Cervero, 2003). Planning interventions in land-use structures and transport provision could, to a extent, promote a modal shift from car transport to more environmental-friendly mobility (Holz-Rau & Scheiner, 2019). However, bicycling has been marginalized in urban transport systems, especially in developing settings where ownership number of motor vehicles increases rapidly (Koglin & Rye, 2014). In this paper, we propose an analytical tool in supporting transport planning and decision-making aiming at bringing bicycle back to city.

First of all, a theoretical framework of underlying linkage is developed to inform the policy makers who are involved in planning formulation procedure. Then, we fully capture land-use characteristics in regard of bicycling using appropriate variables from 3 aspects: land-use types, land-use mix and land-use connections. A set of generalized metrics can be used to assess situations to make reasonable policy goals and identify vulnerable districts as action areas of priorities. Inclusive and versatile, the framework and indicators are not only limited to our case but also applicable to other countries for authorities. Additionally, the spatial regression model has demonstrated superiorities in quantifying the association between land use and bicycle usage, which is a promising analysis framework for transport planning using land allocation tool.

Particularly, this study advances knowledge of new bike sharing service, and the findings provide practicable guidance for transport planning. In our case of Shenzhen, some strategies should be attached more importance. Bicycle infrastructure (e.g., bike lane) is facilitator of bike usage and it needs to be specifically localization given spatial discrepancy. Districts of Baoan, Longhua, Longgang should provide more dedicated lane for cyclers and so is the fleet size and rebalancing management. Owing to frequent rain and sun-intense in Shenzhen, shelters can also be built above footholds. Moreover, as high bike usage is positively related to density of stations, integrating the FFBS with public transport such as designated parking area near stations, should be considered. It is also urgent to reinforce street connectivity, especially the transition to connect bicycles and public transport. The positive effects of land-use mixture suggest that transport planning with consideration of diversified land aids to achieving the goal of bicycling promotion. Lastly, more weight should be put on increasing the green coverage for bicycling recreation.

6 Conclusion

This paper has made an effort on the impact of land use on bicycle usage based on a big data—spatial approach and originally proposed an theoretical framework to reveal the mechanistic associations. Data of 3 metrics in terms of bicycling is scrapped from *Mobike* in Shenzhen, containing frequency, travel duration, and riding distance, to indicate bicycle usage. Land-use characteristics regarding bicycling are comprehensively extracted by a set of standardized land-use variables from 3 dimensions: land-use types, land-use mix and land-use connections. We apply panel spatial model to quantify the impact of land use on bike usage at district level with socioeconomics controlled. The theoretical and methodological

frameworks are not only restricted in our case but also applicable to other cities worldwide. Using a case of Shenzhen in developing China, some key factors are identified: percentage of green land, land-use mix, number of public transport stations. The bicycle usage on weekday is more related with residential land, bicycling lane, while the bicycling at weekend is prone to be observed in commercial land with less time spend, and people in green land tend to ride longer. Our study provides an insight into the interaction between land use and urban transportation. Land use has a significant influence on bicycle usage in frequency, time and distance through the mediator of support, perception, exposure. Thus, the findings give practical guidance for urban transport planning. For example, bicycle lane and shelter should be integrated with public transport, especially the transit stations, to promote bike usage.

Limitations of the current study should also be mentioned. Firstly, the role of personality and cognition between individuals have not been taken into consideration. Secondly, there are uncertainties in evaluating bicycle usage based on a sample of one company. Other providers of FFBS besides *Mobike* should be incorporated into analysis when related data is available. Thirdly, our measurement is conducted at district level, following efforts should explore multi-level or fine spatial scales (e.g., 500m) to better support transport planning. Overall, future studies should enrich and improve land-use factors, investigate dynamic influence of land use on bicycle usage, and extend study area to more specific cases in other cities all over the world.

Acknowledgements

The author thanks anonymous reviewers for their suggestions to improve the manuscript.

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